

An Econometric Analysis of the Enlisted Goaling Model

Dan D. Goldhaber

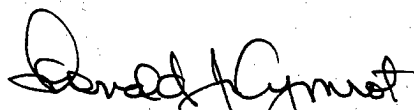
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Summary

Introduction

The Navy uses the Enlisted Goaling Model to predict the supply of net new A-cell recruit contracts. A-cell recruits are high school diploma graduates (HSDGs) who score at or above the 50th percentile on the Armed Forces Qualification Test (AFQT). This model predicts the number of net new enlistment contracts as a function of recent male HSDGs, propensity for joining the military, number of recruiters, recruiting advertising dollars spent, and performance of the civilian economy. Commander, Navy Recruiting Command (CNRC) requested that CNA reexamine and refine the econometric specification of the goaling model to ensure that it was predicting the supply of available recruits with the highest degree of accuracy possible. Specifically, our task was to investigate:

- Whether the current econometric specification of the model is appropriate or whether the inclusion of alternate variables or the use of an alternate functional form increases the accuracy of the model
- Whether the basic form of the model also serves to predict recruit contracts for a higher quality subset of A-cells (namely, HSDGs from AFQT categories I and II)
- Whether the appropriate supply model for workforce recruits is significantly different from the model for high school seniors.

Data

In assessing the model, we use data from 1992 through 1998, supplied by CNRC. The data include all of the variables used by CNRC to estimate the basic form of the A-cell model as well as additional data on

the number of AFQT category I and II recruits, the number of workforce recruits, and the number of high school senior recruits. We augment these data with information on average state tuition in colleges and universities, and several different wage and unemployment measures [1, 2, 3].

Results

In investigating the basic specification of the goaling model, three econometric issues came to our attention:

1. *Extent to which collinearity is a problem.* Collinearity is the degree to which changes in explanatory variables tend to move in sync with one another.
2. *Order of autocorrelation.* Autocorrelation is the relationship between the error terms in any two periods.
3. *Endogeneity of advertising.* Endogeneity of advertising refers to the possibility that there is a correlation between the advertising variable and the error term.

We do not think that the first two merit changing the basic model; however, we do recommend dropping the advertising variable from the model because its inclusion in the model may lead to biased predictions of recruitment.

Next we determine whether we could improve the model fit by substituting or adding variables to the basic model. We find that using alternative variables improves the fit of the A-cell model only slightly.

Finally, we determine what the best model specifications are for the A-cell subpopulations: category I and II recruits, workforce recruits, and high school senior recruits. The fit of each of the subpopulation models is improved with the use of alternative unemployment rate and pay variables, and, in the case of the category I and II and high school senior models, the inclusion of college tuition variables. We find we can better predict the subpopulations (workforce, high school senior, and category I and II recruits) using model specifications that do not restrict the coefficients to those of the A-cell model coefficients. We also conclude that the supply model of AFQT category I and II recruits is significantly different from that for all A-cells.

Conclusion

Other than the elimination of the advertising variable from the model, our recommended changes to the basic specification are small. Though these changes should lead to more accurate predictions, they will not lead to dramatic improvements because the specification of the current goaling model is already quite good.

When trying to make predictions about the subpopulations, we found that estimates from the subpopulation models significantly outperform predictions from the basic form of the A-cell model. Of specific interest, we found that the supply model for workforce recruits is significantly different from the model for high school senior recruits.

Introduction and literature review

The Navy uses a sophisticated econometric model, the Enlisted Goaling Model, to determine the supply of eligible recruits and to allocate recruiting mission across recruiting districts. In the past, this model has predicted relatively accurately the overall number of recruits. Over the past 5 years, the model predictions have differed by less than 10 percent from actual production. However, given the marked change in the civilian labor market in recent years (e.g., the increased college participation rate and the low unemployment rate) and the difficult Navy recruiting mission, CNRC felt it appropriate to reexamine and refine the econometric specification of the goaling model to ensure that it was predicting the supply of available recruits with the highest degree of accuracy possible. Thus, CNRC asked CNA to answer the following questions:

- Is the current econometric specification of the model appropriate, or would the inclusion of alternative variables or the use of an alternative functional form improve the accuracy of the model?
- Does the basic form of the model also serve to predict recruits from AFQT categories I and II?
- Is the appropriate supply model for workforce recruits significantly different from the model for high school seniors?

The Navy's Enlisted Goaling Model grew out of a model that CNA developed almost 20 years ago and documented in [4]. Key among the findings in [4] are the following:

- We have found that recruiters increase *DOD* enlistments and that they are a relatively cost-effective means of increasing supply.
- For recruiting to be successful, military pay and benefits must keep up with those in the private sector on a year-to-year basis,

and the services' recruiting commands need to be able to adjust more quickly to changes in the economy.

Over time, CNRC has modified the Enlisted Goaling Model to incorporate additional variables and change the years of data on which it is run. However, these two findings still generally apply in relation to the current Enlisted Goaling Model.

Other models of enlistment supply or of decisions to enlist are contained in [5, 6, 7, 8]. Of particular note is a more recent RAND study [9], which suggests that recently (FY90-93) the impact of some factors influencing recruiting success has changed from the 1980s (FY83-87). Specifically, the impact of the number of recruiters in the field was smaller in the 1990s than the 1980s for the Army and the Air Force. This study also states that the "estimated model for the Navy ... conforms least well to prior theoretical expectations" (p. 47) and there was "considerable difficulty estimating with confidence the coefficients on pay, bonuses, the Army College Fund and advertising" (p. 52). These points are worth noting because, as we discuss in the next section, we experience similar difficulty in obtaining stable coefficients on some variables and, in some model specifications, our results are counterintuitive.

Data and econometric specification of the model

The Navy uses the Enlisted Goaling Model to predict the number of net new A-cell¹ recruit contracts. These predictions serve (1) as a means of providing warnings of recruiting difficulties so that additional resources, if necessary, can be provided to achieve a specified goal, and (2) to allocate overall Navy recruiting goals across Navy Recruiting Districts (NRDs) in a way that is fair, given demographic differences between NRDs.

The dependent variable in the model is the number of net contracts in a quarter from each NRD. The explanatory variables in the current model are:

- The number of production recruiters in each NRD
- The seasonally unadjusted employment rate
- The ratio of military pay to Civilian Youth (males aged 18 to 25) Earnings
- The propensity to enlist (YATS)
- The combined amount of money spent by the Army and the Navy on advertising
- The number of A-school seats available
- Demographic variables describing the male A- and Cu-cell² populations in each NRD

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1. A-cell recruits are HSDGs who score at the 50th percentile or above on the AFQT.
 2. Cu-cell recruits are HSDGs who score between the 31st and 50th percentile on the AFQT.

- The veteran population in each NRD
- Controls for season, government shutdown in 1995, and individual NRD effects.³

The appendix provides detailed information on data sources and variable definitions.

To account for the possibility of a strong relationship between recruiting in a particular quarter and recruiting in past quarters, the model is estimated as an autoregressive form. Although we will not go into a great deal of detail here about the autoregressive form used to estimate the goaling model,⁴ two additional aspects of the model estimation strategy are worth mentioning. First, the dependent variable and all of the explanatory variables (except the controls for season, government shutdown, and drug testing) are in a logarithmic form such that the coefficients on the explanatory variables provide an indication of the percentage change in net recruits with a given percentage change in an explanatory variable. For instance, if the coefficient estimate on the log of the number of recruiters variable is .5, a 10-percent increase in the number of recruiters is predicted to increase the number of male A-cells by 5 percent. Second, the coefficient estimates on the three population variables (population male A-cell, the ratio of the veteran population to the population of male A-cells, and the ratio of the male Cu-cell population to the male A-cell population) are restricted to sum to 1. The reason for this restriction is that, in some specifications of the model, the magnitude and direction of

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3. The Enlisted Goaling Model includes a dummy variable for the onset of drug testing at MEPS; however, we cannot include this variable because we have missing observations of when drug testing occurred for some subpopulations, and we wish to keep our sample sizes constant across models.
 4. The basic autoregressive form assumes a model in which the dependent variable, Y_t , is a linear function of a vector of explanatory variables, X_t , and an error term, V_t : $Y_t = \beta X_t + V_t$. The error term, V_t , is a function of earlier errors and a mean zero disturbance term, U_t : $V_t = \rho V_{(t-1)} + U_t$. Subtracting $\rho Y_{(t-1)}$ from the left and right sides of the equation and rearranging terms yields $Y_t = \rho Y_{(t-1)} + \beta(X_t - \rho X_{(t-1)}) + U_t$, which is the form of the model that is estimated.

the coefficient estimates on these variables is contrary to expectation in the unrestricted specifications of the model.

CNRC supplied data from 1992 through 1998 for our assessment of the model. These data include all of the variables used by CNRC to estimate the basic form of the A-cell model, as well as additional data on the number of category I and II recruits, the number of workforce recruits, and the number of high school senior recruits. We augment these data with information we collected from outside sources [1, 2, 3]:

- Average tuition (by state) in 4-year public and private colleges and universities (from the Integrated Post Secondary Education Data System)
- Average wages for those with at least an Associate degree and those with at least a Bachelor's degree (from the Current Population Survey)
- Average unemployment rates for individuals with some college but less than a Bachelor's degree and with at least a Bachelor's degree (from the Statistical Abstract of the United States).

We test a number of different econometric specifications of the model, including alternative functional forms and the inclusion of different explanatory variables.

Results

A-cell model

In investigating the basic specification of the goaling model, three econometric issues came to our attention:

1. *Extent to which collinearity is a problem.* Collinearity refers to the correlation among the explanatory variables in multiple regression. It is the degree to which changes in explanatory variables tend to move in sync with one another.
2. *Order of autocorrelation.* Autocorrelation is the relationship between the error terms in any two periods. In the case of the goaling model, it is the relationship of the error term in one quarter to the error terms in previous quarters.
3. *Endogeneity of advertising.* Is it appropriate to include money spent on advertising as an explanatory variable, or is the advertising variable endogenous? Endogeneity of advertising refers to the possibility of a correlation between the advertising variable and the error term. This can happen if the success of recruiting plays a role in determining the level of advertising.

Collinearity

One common sign of serious collinearity is when a statistical model explains a very high proportion of the variation in the dependent variable (a high R^2), but few of the explanatory variables have statistically significant coefficients. With a highly collinear model, it is also possible to find a high R^2 and highly significant coefficient estimates (t values); however, the magnitude and signs of these coefficient estimates are often very sensitive to model specification [10]. The concern with collinearity here arises from several puzzling findings. First, when they are not restricted to sum to 1, the signs on the coefficients of the population variables are very sensitive to model specification

and are sometimes contrary to expectations. This means that the model, in some cases, predicts fewer A-cell recruits in NRDs with higher A-cell populations. Second, all of the model results are extremely sensitive to the inclusion of fiscal year 1992 in the data.

To determine the degree to which collinearity may explain these strange results, we obtained collinearity diagnostics. These showed that several of the included variables (the population variables and several of the NRD dummy variables) are, in fact, highly collinear. Although this collinearity inflates the standard errors and causes the unstable coefficient estimates, it does not otherwise affect the model. Thus, neither the coefficient estimates nor the predicted values from the model are biased. Having said that, collinearity does limit the functional form of the model in important ways. For instance, we attempted to determine whether a change in unemployment at low levels of unemployment has the same effect on recruiting as an equal change at a higher level of unemployment. For instance, one might guess that a change in the unemployment rate from 10 to 9 percent would have a different effect than a change from 5 to 4 percent—that is, the relationship is nonlinear. The standard way to test this hypothesis is to include squared terms for those variables of interest. Unfortunately, these squared terms are an additional source of collinearity and lead to greater instability of the predicted coefficients. Thus, we were unable to assess the degree to which there are nonlinearities in the basic model.

In the case of the population variables, the imposed restriction (that the coefficients sum to 1) seems to solve the problem, but there is no theoretical basis for this restriction. However, a specification test (F-test) indicates that the restricted version of the model is not significantly different from the unrestricted version of the model. And, the difference in explanatory power between the restricted and unrestricted versions of the model is negligible with the explained portion of the variation in the dependent variable (R^2) falling only from .7542 to .7531. In other words, we see no significant problem with this restriction, which does lead to more sensible results. Therefore, we do not object to the continued use of this restriction, even though the restriction is arbitrary.

Unfortunately, collinearity problems are not easy to fix. One potential solution is to replace one or more variables that are collinear with one another with variables that are correlated with the ones they replace but not with one another. This might mean replacing a population variable (e.g., veteran population) with another variable that proxies for veteran population but is not so highly correlated with the NRD variables. In practice, it is very difficult to find these "replacement" variables. A second solution is to simply drop some of the variables that are collinear from the model. Because these variables tend to track closely with one another, the model loses little explanatory power if some of them are dropped. Probably the best solution is to collect more data and hope that the additional data are less collinear.

CNRC expressed some concern that the use of older data might lead to poor predictions if there were structural changes in the recruiting market. While this is a legitimate concern, it is possible to test whether this concern is applicable (i.e., whether structural change has occurred). In the absence of evidence of this, we *recommend that CNRC adopt the strategy of using data for more than the current custom of 6 years*. The bottom line is that collinearity does not cause bias in the coefficient estimates or model predictions. To the extent that the goaling model is being used to allocate the specific resources that are in the model, however, it is necessary to deal with the problem of collinearity because the point estimates (coefficients) are not likely to be very stable.

Autocorrelation

The current model specification assumes that the error term in one quarter is correlated to the immediate prior quarter's error term. This is known as first-order autocorrelation. It is also possible, however, that the error term in one quarter is related to error terms in earlier quarters, which is higher order autocorrelation. The Durbin-Watson specification test reveals first- and fourth-order autocorrelation. This implies that the current quarter's error is correlated with the errors in the immediate previous quarters as well as the error term in the quarter one year earlier.

It is possible to correct for higher orders of autocorrelation. In this context, however, it makes very little difference whether this correction is made. Autocorrelation, if no correction is made, does result in less accurate predictions and coefficient estimates, but it does not cause bias in either of these. And, in this case, the difference in the accuracy of the predictions is minimal. We find that the R^2 drops from .7577 when the correction for higher order autocorrelation is made to .7531 when we correct only for first-order autocorrelation. Because many statistical packages (including LIMDEP) do not correct for higher order autocorrelation, and the correction makes very little difference in terms of explanatory power, we would *recommend continuing to correct for first-order autocorrelation only*.

Endogeneity of advertising

The concern about the advertising variable arises from the fact that, in several specifications of the model, the sign on the advertising variable is negative. This implies that increases in advertising actually decrease recruiting success—clearly a counterintuitive finding. One possible reason for the unusual finding is that propensity is already in the model and the effect of advertising on recruitment may only be an indirect effect through the influence of advertising on propensity. In addition, we hypothesize that our findings do not really represent the effect of advertising on recruiting; rather, we are observing the opposite—the effect of recruiting success on the level of advertising expenditure. The implication is that, the more difficult it is to find qualified recruits, the more money the Navy (and Army) will spend on advertising.

Even if current recruiting success does not influence current advertising, the advertising variable is still potentially problematic in this model because it has an autoregressive form implying that lagged exogenous variables are included as right-hand-side regressors. As a result, endogeneity may exist even if past recruiting success affects the amount of money spent on current advertising. If this is the case, the advertising variable is not exogenous, and it is inappropriate to include it as an explanatory variable in the model because it will lead to biases in coefficient estimates and model predictions.

We test the hypothesis that advertising is an endogenous variable by estimating a model in which advertising is the dependent variable and current and past net A-cell recruits are the explanatory variables.⁵ We find that both current and past recruiting success are statistically significant in predicting advertising spending. Further, the coefficients on current and past recruiting are negative, which is consistent with the hypothesis that advertising spending increases when the Navy is less successful in its recruiting efforts. These results clearly suggest that recruiting success does influence advertising spending. Because the advertising variable does not provide a statistically significant contribution to explaining recruiting success in this model, and because it is difficult to correct for the problem of endogeneity, we *recommend dropping advertising from the model*.

The effect of advertising on recruitment is no doubt important to identify, particularly if the point estimate on the advertisement variable is used to make policy decisions regarding investments in advertising. Given the potential problems we described, however, this is a difficult relationship to accurately assess. We suggest the development of a model that deals explicitly with the impact of advertising on recruitment. As suggested above, advertising may only indirectly affect recruiting through propensity, so a first step would be to see if spending on advertising affects propensity. In particular, we would suggest estimating propensity as a function of current county population and labor market characteristics and past advertising expenditures in the local area.⁶ Such a model also has an intuitive appeal because both advertising and propensity are servicewide measures and thus would be aligned at the appropriate level of aggregation. Having calculated the impact of advertising on propensity and propensity on enlistment (from the current model), it would be possible

5. In this model, we also include propensity (YATS), A-school seats, and dummy variables for quarter, government shutdown, and drug testing.

6. Past expenditures should be used rather than current expenditures to avoid the potential for endogeneity. Also, we might expect monies spent on advertising to have a somewhat delayed impact on propensity, given that monies spent on advertisements may not immediately translate into advertisements.

to estimate the indirect effect of marginal changes in advertising spending on enlistment.⁷

Alternative variables

One of the tasks in this analysis is to determine whether any additional or alternative variables could better predict A-cell recruiting success. We felt that the following variables might be worth including (or substituting for other variables) in the model. These are the log values of:

- Military pay relative to civilian pay for those with at least an Associate degree
- Military pay relative to civilian pay for those with at least a Bachelor's degree
- The unemployment rate for those with some college but no degree
- The unemployment rate for those with at least a Bachelor's degree
- Average tuition, by state, for public and private schools.

These are all variables that we felt might be relevant to people who are making the decision to enter the Navy or pursue a civilian alternative (i.e., going to college or obtaining a job).

The unemployment and relative pay variables are substituted in place of the unemployment (for all civilian workers) and pay (for all civilian workers) variables currently in the model. The tuition variables are used in addition to the variables included in the basic model. Because all of these variables are available from readily accessible sources [1, 2, 3], obtaining these variables would not impose an additional burden on Recruiting Command should it prove worthwhile to include one or more of these variables in the goaling model.

7. It may also be possible to estimate the direct impact of monies spent on advertising on recruiting; however, it would be a complex two-stage process that would be quite data intensive.

Table 1 shows the predictive power (R^2) of various model specifications. Surprisingly, the substitute pay variables do not improve the fit of the model, and the improvement in the fit of the models associated with the inclusion of the tuition variables is not statistically significant.⁸ We do find that each model with one of the alternate unemployment rates does explain a statistically significantly higher portion of the variance in net A-cell recruits than does the base model. However, the use of each alternative unemployment rate causes the coefficient on the unemployment rate variable to change from the expected sign (positive) to the counterintuitive sign (negative). Although it would enhance the overall predictive power of the goaling model, the difference in fit is relatively small from substituting an alternative unemployment rate variable. For these reasons, we *do not recommend changing the mix of variables currently used in the Enlisted Goaling Model*.

Table 1. Statistical significance of various A-cell model specifications

	R^2
Base model	0.7680
Model with (military/Associate degree) pay	0.7665
Model with (military/BA) pay	0.7664
Model with some college unemployment rate	0.7720
Model with BA unemployment rate	0.7694
Model with public & private tuition	0.7732

Econometric models for A-cell subpopulations

In this subsection, we describe the results of our estimates of the A-cell subpopulations: AFQT category I and II recruits, workforce recruits, and high school senior recruits. First, we determine the

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8. The inclusion of additional variables in a regression always improves the R^2 . We perform an F-test to determine whether this improvement in the R^2 represents a statistically significant difference. We could not reject (at the 5-percent level) the null hypothesis that the coefficients on the tuition variables are jointly equal to zero.

extent to which each subpopulation can be predicted from the overall A-cell population. In other words, we are interested in whether the success in recruiting these subpopulations can be predicted, with a relatively high degree of accuracy, based on current or past A-cell recruiting success. Next, for each of the subpopulation models, we determine which of the alternative variables (discussed earlier) provides the best fit for the models. Finally, we explore whether estimating the subpopulations separately represents a statistically significant improvement over simply estimating these subpopulations using the A-cell model results.

Using A-cell success to predict subpopulation success

Table 2 shows the estimated coefficients and explanatory power (R^2) when we estimate the number of subpopulation recruits using the number of A-cell recruits. The table also reports the coefficients when we use the lagged number of A-cell recruits as our explanatory variable.⁹

Table 2. Estimates of the number of subpopulation recruits using the number of A-cell recruits as the primary exogenous variable (absolute value of t-statistic)

	Subpopulation		
	Category I & II	Workforce	High school senior
A-cell recruits			
Coefficients	0.896 (35.1)	0.772 (25.6)	1.411 (30.1)
R^2	0.7587	0.7073	0.6283
Lagged A-cell recruits			
Coefficients	0.568 (15.3)	0.233 (5.7)	1.203 (21.6)
R^2	0.4307	0.4436	0.4076

9. All models include NRD fixed effects and are estimated in an autoregressive form.

For each subpopulation, the coefficient of current A-cell recruits is highly significant, and the number of subpopulation recruits is predicted relatively accurately, with R^2 values ranging from 0.63 to 0.76. However, the lagged value of A-cell recruits, though statistically significant, does a far worse job of predicting the current value of subpopulation success. Roughly speaking, the lagged value of A-cell recruits explains only about half of the variation that the current value of A-cell recruits explains. In addition, the lagged value of A-cell recruits does not predict subpopulation success as well as the full model described below. Thus, if the subpopulation models can't be estimated separately, we think it is appropriate to use current-quarter A-cell recruits to predict the number of subpopulation recruits.

Alternative variables in the subpopulation models

Following the procedure we used to determine the appropriate model specification for A-cell recruits, we determine which alternative variables to include in the subpopulation models to generate the most accurate predictions. Table 3 shows the predictive power (R^2) of alternative specifications of the subpopulation models.

Table 3. Predictive power of various subpopulation model specifications

	R^2		
	Category I & II	Work-force	High school senior
Base model	.7096	.6906	.6237
Model with (military/1-3 years college) pay	.7148	.6924	.6245
Model with (military/BA) pay	.7147	.6932	.6244
Model w/ 1-3 years college unemployment rate	.7347	.7038	.6734
Model with BA unemployment rate	.7229	.6739	.6581
Model with public & private tuition	.7275	.6943	.6398

Like the A-cell model, the fit of the subpopulation models improves with the use of the alternative unemployment rate variables—at the cost of changing the coefficient's sign from positive to negative. However, unlike the case with the A-cell model, we find that the model

specifications with the alternative pay measures improve the fit of each of the subpopulation models. The inclusion of the tuition variables improves the fit of the category I and II model and the high school senior model, but does not improve the fit of the base workforce model. These results are quite sensible when one considers the civilian alternatives faced by these subpopulations. People in AFQT categories I and II are much more likely to go to college, if they do not enter the military, than the A-cell population as a whole, so it makes sense that they would be more affected by changes in tuition. Similarly, we would argue that college tuition is likely to be more relevant to high school senior recruits than to workforce recruits.

Subpopulation models versus single A-cell model

For each of these subpopulations, we would like to test whether estimating the subpopulation separately represents a statistically significant improvement over simply estimating these subpopulations using the A-cell model results. For instance, it is plausible that the predictions derived from the coefficient estimates generated from estimating the (workforce) model separately from the A-cell model are not significantly different from the predictions that could be derived if the estimated coefficients from the A-cell model are used to estimate the subpopulation (workforce). We test the hypothesis that the coefficients of the male A-cell population, recruiters, relative pay, and propensity are significantly different between the A-cell model and each subpopulation model. This specification test (an M-test) is performed by restricting the coefficients in each of the subpopulation models to those estimated for the A-cell model and comparing the joint significance of the restricted model to the unrestricted model (this is described more formally in the appendix).¹⁰ For each subpopulation, the restriction of the coefficients to those of the A-cell coefficients causes a statistically significant decrease in the explanatory power of the model. This means that estimating the subpopulation models separately from the A-cell model will lead to predictions that significantly outperform the predictions when the coefficients from the A-cell model are used to predict recruits from the subpopulations.

10. The M-test is used to test hypotheses in multivariate models that have several dependent variables fit to the same regressors. It is similar to the F-test in a single model.

We conclude that, when trying to predict behavior within one of the subpopulations, it is appropriate to allow the coefficients of these models to differ from those of the A-cell model. Doing so will lead to predictions that significantly outperform the predictions when the coefficients from the A-cell model are used to predict recruits from the subpopulations.

High R^2 econometric specifications

Table 4 shows the coefficient estimates from the model specifications with the highest R^2 values (the specifications that maximize the predictive power of the models) for each of the recruit populations (A-cell, category I and II, workforce, and high school senior) and compares them to the coefficients from estimating the A-cell recruits using the base model (in column 1). Some coefficient estimates are more sensible in the base model than in the models that have the maximum predictive power. For instance, consistent with CNRC's model, we found that the sign on the general civilian unemployment rate was positive in the base model, indicating that recruiting is more successful when the civilian economy is poor (i.e., there is high unemployment). This is the expected result. When we use the unemployment rate for those with 1 to 3 years of college (in column 2), however, we get the counterintuitive finding (a negative coefficient on the variable) that recruiting becomes more difficult when the unemployment rate is high.¹¹ This result occurs in the category I and II and workforce models as well.¹²

The econometric specification that is most appropriate to use will depend, in part, on the specific uses of the model being estimated. The goaling model is used primarily to predict the number of net new A-cell recruit contracts to 1) provide warnings of potential recruiting difficulties and 2) allocate recruiting goals fairly across NRDs. If all

11. This finding is likely a result of the collinearity of the data.

12. It is worth noting that, though these findings are counterintuitive, they are consistent with some of the findings in [9], which also reports coefficient estimates (for the Navy model) on unemployment that are counterintuitive.

the model was used for was the first purpose, which is essentially to predict overall enlistment for the nation as a whole, it would make sense to use the specification of the model that has the highest R^2 , regardless of the values of individual coefficients. However, the model is also used to allocate goals across NRDs, and the coefficient estimates have to be explained to nontechnical audiences. For these reasons, and because the gains in R^2 from using the alternative model specifications that have counterintuitive signs are very slight, we recommend using specifications that have slightly lower predictive power but commonsense coefficient estimates. The coefficient estimates from these "preferred" models are reported and compared in the following subsection.

Table 4. Model specifications with highest R^2 (value of t-statistic)^{a, b}

Variable	(1) A-cell base model	(2) A-cell	(3) Category I & II	(4) Workforce	(5) High school senior
Intercept	-8.09 (-1.6)	-19.59 (-3.6)	-38.06 (-3.3)	-32.93 (-4.3)	-14.80 (-0.8)
Male A-cell population	1.51 (1.2)	1.31 (3.0)	2.30 (3.6)	2.19 (3.6)	0.31 (0.3)
(Vet pop)/(male A-cell pop)	2.71 (6.4)	3.93 (8.8)	5.33 (6.4)	5.40 (8.7)	3.52 (2.5)
(CU pop/male A-cell pop)	-2.22 (-3.3)	-4.25 (-5.8)	-6.63 (-5.0)	-6.59 (-6.5)	-2.83 (-1.3)
Production recruiters	0.29 (3.6)	0.33 (4.1)	0.26 (2.9)	0.15 (1.4)	0.33 (2.4)
Unemployment rate ^c	0.16 (1.8)	-0.43 (-3.3)	-0.34 (-2.4)	-1.09 (-6.3)	1.31 (5.1)
(Military pay/civilian pay) ^d	0.54 (1.9)	0.92 (3.2)	-0.05 (-0.4)	0.11 (0.9)	0.04 (0.2)
Propensity	-0.02 (-0.2)	0.05 (0.4)	-0.10 (-0.8)	0.00 (0.0)	-0.08 (-0.4)

Table 4. Model specifications with highest R² (value of t-statistic)^{a, b} (continued)

Variable	(1) A-cell base model	(2) A-cell	(3) Category I & II	(4) Workforce	(5) High school senior
A-school requirement	1.08 (8.5)	0.95 (7.4)	0.74 (4.8)	0.62 (3.4)	2.31 (9.1)
2nd quarter	0.07 (3.1)	0.08 (4.1)	0.14 (6.5)	0.10 (4.1)	0.09 (2.3)
3rd quarter	-0.11 (-5.2)	-0.10 (-5.0)	0.14 (5.7)	0.18 (6.7)	-0.27 (-6.2)
4th quarter	0.10 (4.7)	0.11 (5.7)	0.26 (9.4)	0.35 (13.2)	-0.15 (-3.1)
Federal shutdown	-0.21 (-4.5)	-0.16 (-3.4)	-0.04 (-0.8)	-0.05 (-0.8)	-0.29 (-3.2)
Average private tuition	NA	NA	-0.20 (-0.4)	NA	-0.03 (-0.0)
Average public tuition	NA	NA	0.55 (2.1)	NA	0.65 (1.5)
Autocorrelation coefficient	0.18 (3.7)	0.18 (3.9)	0.19 (3.8)	0.20 (4.1)	0.03 (0.6)
Degrees of freedom	437	437	403	405	403
R ²	0.7680	0.7739	0.7318	0.7029	0.6712

a. All models include NRD fixed effects and are estimated in an autoregressive form.

b. All continuous variables are in log form.

c. The unemployment rate for the A-cell base model is the overall civilian unemployment rate. The unemployment rate for the other models is the unemployment rate for people with some college experience.

d. The relative pay for both A-cell models is the relative pay of military personnel to all civilians. The relative pay for the category I and II and high school senior models is the relative pay of military personnel to civilians with at least an Associate degree. The relative pay for the workforce model is the relative pay of military personnel to those with at least a Bachelor's degree.

Preferred specification and comparison of policy variables

Table 5 shows the results of model specifications that have a combination of good predictive power and sensible coefficient estimates. These specifications are not necessarily the ones that maximize predictive power; however, the difference in R^2 between these specifications and those listed in table 4 is minor. The preferred A-cell specification is the A-cell base model.

Table 5. Preferred model specifications (value of t-statistic)^{a, b}

Variable	(1) A-cell base model	(2) Category I & II	(3) Workforce	(4) High school senior
Intercept	-8.09 (-1.6)	-32.44 (-3.0)	-10.51 (-1.7)	-14.80 (-0.8)
Male A-cell population	1.51 (1.2)	1.98 (3.4)	0.83 (1.6)	0.31 (0.3)
(Vet pop)/(male A-cell pop)	2.71 (6.4)	3.81 (5.3)	2.24 (6.3)	3.52 (2.5)
(CU pop/male A-cell pop)	-2.22 (-3.3)	-4.79 (-4.0)	-2.07 (-2.9)	-2.83 (-1.3)
Production recruiters	0.29 (3.6)	0.33 (4.0)	0.17 (1.7)	0.33 (2.4)
Unemployment rate ^c	0.16 (1.8)	0.13 (1.4)	0.16 (1.5)	1.31 (5.1)
(Military pay/civilian pay) ^d	0.54 (1.9)	0.39 (1.5)	0.15 (1.4)	0.04 (0.2)
Propensity	-0.02 (-0.2)	-0.07 (-0.6)	-0.09 (-0.7)	-0.08 (-0.4)
A-school requirement	1.08 (8.5)	0.95 (8.2)	0.94 (6.7)	2.31 (9.1)

Table 5. Preferred model specifications (value of t-statistic)^{a, b} (continued)

Variable	(1) A-cell base model	(2) Category I & II	(3) Workforce	(4) High school senior
2nd quarter	0.07 (3.1)	0.10 (4.4)	0.08 (2.9)	0.09 (2.3)
3rd quarter	-0.11 (-5.2)	0.12 (5.2)	0.16 (6.9)	-0.27 (-6.2)
4th quarter	0.10 (4.7)	0.25 (9.7)	0.33 (14.8)	-0.15 (-3.1)
Federal shutdown	-0.21 (-4.5)	-0.13 (-3.7)	-0.15 (-3.5)	-0.29 (-3.2)
Average private tuition	NA	0.01 (0.0)	NA	-0.03 (-0.0)
Average public tuition	NA	0.54 (2.3)	NA	0.65 (1.5)
Autocorrelation coefficient	0.18 (3.7)	0.22 (4.8)	0.23 (5.3)	0.03 (0.6)
Degrees of freedom	437	481	509	403
R ²	0.7680	0.7187	0.6932	0.6712

a. All models include NRD fixed effects and are estimated in an autoregressive form.

b. All continuous variables are in log form.

c. The unemployment rate for the A-cell model, the category I and II model, and the workforce model is the overall civilian unemployment rate. The unemployment rate for the high school senior model is the unemployment rate for people with some college experience.

d. The relative pay for the A-cell model and the category I and II model is the relative pay of military personnel to all civilians. The relative pay for the high school senior models is the relative pay of military personnel to civilians with at least an Associate degree. The relative pay for the workforce model is the relative pay of military personnel to those with at least a Bachelor's degree.

There are some interesting differences in coefficients between models. For instance, the coefficient on 3rd quarter is negative and significant for high school senior and overall A-cell recruits but positive and significant for category I and II and workforce recruits. Many of the variables in the models are variables over which the Navy has no

control (e.g., quarter, government shutdown, propensity to enlist). But the Navy does control one variable that was shown to be an important predictor of recruiting success for each population group—the number of production recruiters assigned to each NRD. In general, we found a significant degree of collinearity across the explanatory variables, making our coefficient estimates unstable. When we performed collinearity diagnostics, however, the number of production recruiters was not very collinear with the other explanatory variables in the model. Thus, its coefficient estimates are stable enough to allow comparison. We compare the coefficient on the number of production recruiters in each of the models to determine how the magnitude of the coefficient differs for each A-cell subpopulation. This should provide an indication of the relative effectiveness, and thus cost, of using recruiters to recruit these subpopulations.

The coefficient on recruiters (.33) is the same for the A-cell recruits (in column 2) and the high school seniors (in column 5); however, it is slightly larger than the coefficient in the category I and II model (.26) and more than twice as large in the workforce model (.15). The difference between the A-cell coefficient and the category I and II coefficient is not of a large magnitude, but the large difference between the A-cell and workforce models implies that a given percentage increase in the number of recruiters will increase the percentage of A-cells by more than twice as much as it will increase workforce recruits. However, this may simply be a reflection of the allocation of recruiters' time across the two markets. To put these numbers in perspective, there were about 4,000 recruiters who recruited 3,800 A-cell recruits from the workforce and 2,600 A-cell recruits out of high school in the second quarter of 1997. An increase of 10 percent, or 400 recruiters, is predicted to increase high school senior recruits by 3.3 percent, or 86. However, it is predicted to increase the number of workforce recruits by only 1.5 percent, or 57.

Comparing the magnitudes derived from these coefficients (57 vs. 86) would suggest that a recruiter can produce more recruits in the high school market than in the workforce, but only if recruiters are now devoting as much time or more to the workforce market as they are to the high school senior market. Currently, the phasing of recruiting goal across the months of the recruiting year requires

recruiters to devote a significant proportion of their time to the workforce market, but further research is needed to estimate what that proportion is. We will explore these issues in a forthcoming CNA project that analyzes the costs and benefits of level-loading accessions throughout the year versus loading more accessions in the summer and fall. More level loading imposes costs on recruiting, whereas less level loading imposes costs on the training establishment. The most difficult recruiting months of February, March, April, and May (the FMAM months) are made more difficult with level loading. Not coincidentally, almost every accession in the FMAM months is a workforce recruit, and most of the summer accessions are high school senior recruits.

Conclusion

The basic form of the Enlisted Goaling Model has functioned well in the past. We would recommend only small changes to the model. The most important change is the elimination of the advertising variable. There is good reason to believe from a theoretical perspective that this variable is not truly exogenous, and our empirical work suggests that this is, in fact, the case. We would also suggest that CNRC use all of the available years of recruiting data when estimating the goaling model. This should lead to the most accurate predictions and should alleviate some of the collinearity issues.

We have noted that, for each of the population groups, there are substitute or additional variables that slightly improve the fit of the model. These changes should lead to more accurate predictions; however, they will not lead to dramatic improvements given that the specification of the current goaling model is already quite good.

Finally, we found that we can better predict the subpopulations (workforce, high school senior, and category I and II recruits) using model specifications that do not restrict the coefficients to those of the A-cell model coefficients.

Appendix: Data and statistical tests

Data sources

We use recruiting data from 1992 through 1998, supplied by CNRC. The data on the number of recruits in each category (our dependent variables) and the data used to predict recruiting supply (our explanatory variables) are maintained by CNRC. We augment these data with information on average state tuition in colleges and universities and several different wage and unemployment measures [1, 2, 3].

Variable definitions

Table 6 provides definitions of our variables.

Table 6. Variable definitions

Variable	Definition	Level of aggregation
Male A-cell population	The number of high school diploma graduates who score between the 31st and 50 th percentile on the AFQT test	NRD
Category I and II population	The number of net contracts in AFQT category I and II per quarter from each NRD	NRD
Workforce population	The number of net A-cell per quarter recruited from the workforce	NRD
High school senior population	The number of net A-cell per quarter recruited from high school	NRD
(Vet pop)/(male A-cell pop)	The ratio of male veteran population to male A-cell population	County
(CU pop/male A-cell pop)	The ratio of male Cu-cell population to male A-cell population	County

Table 6. Variable definitions (continued)

Variable	Definition	Level of aggregation
Production recruiters	The number of production recruiters	NRD
Unemployment rate ^a	The seasonally unadjusted employment rate	State/national
(Military pay/civilian pay) ^b	The ratio of military pay to civilian youth (males aged 18 to 25) pay	State
Propensity	The 3-year moving average of the propensity for the male A-cell population to enlist in any service	National
Advertising	The combined amount of money spent by the Army and the Navy on advertising	National
A-school requirement	The number of A-school seats available	National
2nd quarter	A dichotomous variable identifying the 2 nd quarter	—
3rd quarter	A dichotomous variable identifying the 3 rd quarter	—
4th quarter	A dichotomous variable identifying the 4 th quarter	—
Federal shutdown	A dichotomous variable identifying the government shutdown in the fall of 1995	National
Average private tuition	The average private school tuition	State
Average public tuition	The average public school tuition	State

a. Depending on model specification, the unemployment rate is either the overall civilian unemployment rate (by state), the national unemployment rate for people with some college experience but no degree, or the national unemployment rate for those with a Bachelor's degree.

b. Depending on model specification, the relative pay is either the military pay relative to civilian pay for people with at least an Associate degree, the military pay relative to civilian pay for those with at least a Bachelor's degree, or the military pay relative to all civilians.

The M-test

The M-test is used to test hypotheses in multivariate models in which there are several dependent variables fit to the same regressors. Formally, the test is:

$$(L\beta - cj)M = 0 ,$$

where L is a linear function on the regressor side, b is a matrix of parameters, c is a column vector of constants, j is a row vector of ones, and M is a linear function on the dependent side. For more information on this procedure, see [11].

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